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[1] There is increasing interest in using Gravity Recovery and Climate Experiment (GRACE) satellite data to remotely monitor groundwater storage variations; however, comparisons with ground-based well data are limited but necessary to validate satellite data processing, especially when the study area is close to or below the GRACE footprint. The Central Valley is a heavily irrigated region with large-scale groundwater depletion during droughts. Here we compare updated estimates of groundwater storage changes in the California Central Valley using GRACE satellites with storage changes from groundwater level data. A new processing approach was applied that optimally uses available GRACE and water balance component data to extract changes in groundwater storage. GRACE satellites show that groundwater depletion totaled ~31.0 ± 3.0 km^3 for Groupe de Recherche de Geodesie Spatiale (GRGS) satellite data during the drought from October 2006 through March 2010. Groundwater storage changes from GRACE agreed with those from well data for the overlap period (April 2006 through September 2009) (27 km^3 for both). General correspondence between GRACE and groundwater level data validates the methodology and increases confidence in use of GRACE satellites to monitor groundwater storage changes.

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1. Introduction

[2] Water scarcity is a critical issue globally with an estimated 1.1 billion people lacking access to safe drinking water globally [*United Nations Development Program*, 2006]. Groundwater is increasingly being used for drinking water and serves an estimated 1.5–2.8 billion people globally and up to 98% of rural populations [*Morris et al.*, 2003]. There has been a rising trend in groundwater use for irrigation since the 1940s and 1950s, and groundwater now accounts for ~40% of irrigation water globally [*Siebert and Döll*, 2010]. Increasing reliance on groundwater for drinking water and irrigation is attributed to ubiquity of groundwater resources, ease of development with minimal capital costs, generally good water quality because of filtering during recharge, and greater resilience to drought relative to surface water [*Giordano*, 2009]. The importance of groundwater to water resources should continue to increase with projected reductions in reliability of surface water and soil moisture associated with climate extremes related to climate change [*Kundzewicz and Döll*, 2009].

[3] Groundwater is often referred to as the invisible resource, and our understanding of the dynamics of groundwater resources is generally much less than that of surface water. Monitoring networks for groundwater are more limited than those of surface water. Even when monitoring networks are available, access to data is often restricted. Because of the general lack of monitoring data, there has been great interest in use of remote sensing to monitor changes in groundwater storage, specifically in use of GRACE satellites. GRACE consists of two satellites that track each other at a distance of ~220 km and are ~450 km above the land surface. A rule of thumb for estimating GRACE footprint is to use the elevation of the satellites (450 × 450 km = ~200,000 km^2 basin area). Measurements of the distance between the satellites to within micron scale resolution are used to derive a global map of changes in the Earth's gravity field at 10 day to monthly intervals. Gravity variations at monthly to annual timescales may be interpreted as changes in water distribution on the continents after correction for impacts of tidal, atmospheric, and oceanic contributions [*Bettadpur*, 2007; *Bruinsma et al.*, 2010].

[4] GRACE data provide vertically integrated estimates of changes in total water storage (TWS), which include changes in snow water equivalent storage (SWES), surface water reservoir storage (RESS), soil moisture storage (SMS), and groundwater storage (GWS). Using a priori monitoring or model-based estimates of SWES, RESS, and SMS, changes in GWS can be calculated as a residual from the disaggregation equation: $\Delta GWS = \Delta TWS - \Delta SWES - \Delta RESS - \Delta SMS$.

[5] GRACE satellites provide continuous monitoring of TWS changes globally. GRACE has been used to monitor GWS changes in global hotspots of depletion [*Wada et al.*, 2010] in NW India [*Rodell et al.*, 2009; *Tiwari et al.*, 2009], U.S. High Plains [*Strassberg et al.*, 2007; *Longuevergne et al.*, 2010], and in the California Central Valley

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[*Famiglietti et al.*, 2011]. However, with the exception of the High Plains, where detailed groundwater level monitoring has been conducted since the 1980s in ~9000 wells annually [*McGuire*, 2009], GRACE-based estimates of GWS have not been compared with ground-based data in NW India or in the Central Valley. Other studies that have compared GRACE data with groundwater level monitoring data have generally focused on seasonal signals rather than long-term trends and groundwater level data have generally been limited to ≤100 wells [*Yeh et al.*, 2006; *Rodell et al.*, 2007; *Moiwo et al.*, 2009].

[6] GRACE satellites provide a spatially filtered image of real TWS that needs to be processed to produce information on changes in TWS over a space-limited area or basin [*Swenson and Wahr*, 2002; *Klees et al.*, 2008; *Longuevergne et al.*, 2010]. A large number of processing steps and uncertainties in other water balance components used to estimate changes in GWS from TWS make it imperative to compare GRACE GWS changes with ground-based data to assess their validity, especially when the size of the area of interest is close to or below GRACE footprint (~200,000 km^2) [*Yeh et al.*, 2006]. Ground-based estimates of GWS changes are generally derived from water table or potentiometric surface fluctuations and require information on aquifer storage coefficients to translate water level fluctuations to water storage [*Domenico and Schwartz*, 1998].

[7] The primary objective of this study was to compare GRACE-based estimates of GWS changes in the Central Valley of California with ground-based estimates from water-level data from wells to assess reliability of GRACE-based estimates of groundwater depletion. Secondary objectives include use of an updated processing approach for GRACE data that considers spatial variability in water balance components and should reduce uncertainties in GWS and evaluation of different temporal filters for estimation of long-term trends in storage for GRACE data. The area of the Central Valley (52,000 km^2) is below the limit of GRACE footprint (~200,000 km^2); however, large mass changes in the aquifer as a result of irrigation pumpage allow storage changes to be detected by GRACE. The Central Valley is an extremely important region for agricultural productivity in California and in the U.S. with an economic value of ~20 billion dollars in 2007 (NASS, 2007; http://www.nass.usda.gov/, accessed in 2010). Because this region plays a large role in table food production in the U.S., it is critical to understand the dynamics of the groundwater system, which is essential for irrigated agriculture, particularly in the Tulare Basin in the south. Previous groundwater modeling shows large-scale depletion during droughts [*Faunt*, 2009]; therefore, the recent drought from ~2006 through 2009 should provide a large signal for GRACE analysis. This study expands on the recent analysis of GRACE data for the Central Valley described in the work of *Famiglietti et al.* [2011] by comparing results from GRACE-based estimates of GWS changes with those from groundwater level data and using a different processing approach.

2. Methods

2.1. GRACE Data

[8] Water storage changes were estimated for the Sacramento and San Joaquin River basins (154,000 km^2 area), which include the Central Valley (52,000 km^2 area) (Figure 1). GRACE data from Center for Space Research (CSR, University of Texas at Austin) and Groupe de Recherche de Geodesie Spatiale (GRGS) analysis centers were used because they represent two different processing strategies: one of the least constrained solutions, CSR RL04 [*Bettadpur*, 2007], and one of the most constrained, GRGS RL02 [*Bruinsma et al.*, 2010]. Comparison of these two products allows estimation of the confidence in GRACE-derived water storage changes. CSR provides data at monthly intervals and GRGS at 10 day intervals. The GRACE processing approach was updated in this study relative to the regular processing approach applied in most studies. The section 2.2 describes the regular processing approach, which provides context for the updated approach.

2.2. Regular GRACE Processing

[9] The regular processing approach estimates changes in TWS from GRACE data by filtering the data, applying corrections for bias and leakage [*Swenson et al.*, 2002; *Klees et al.*, 2008; *Longuevergne et al.*, 2010] and solving the disaggregation equation to calculate changes in GWS

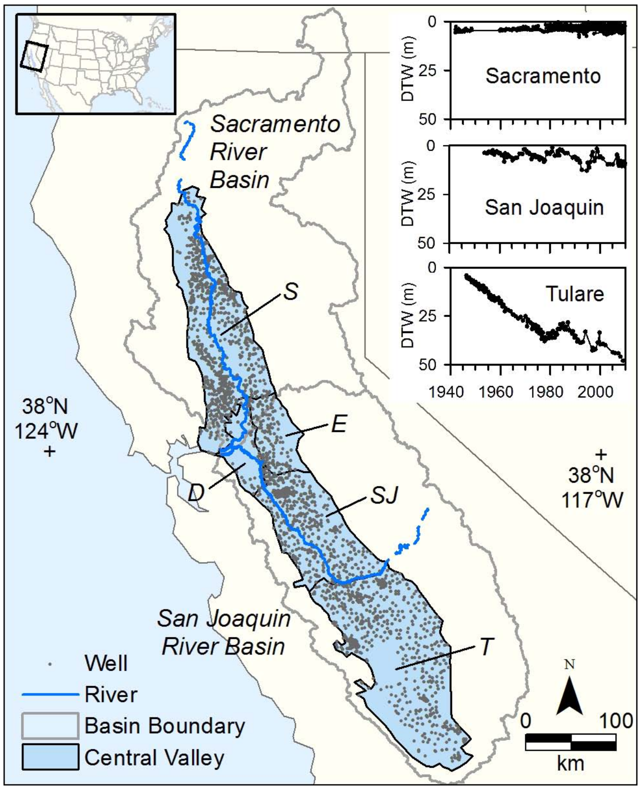

Figure 1. Central Valley aquifer subdivided into Sacramento, Delta, Eastside, San Joaquin, and Tulare basins and enclosed in the Sacramento River Basin in the north and San Joaquin River Basin in the south. Distribution of monitoring wells (~2300 wells) is also shown. Well data were obtained from the California Department of Water Resources. Typical well hydrographs are shown for the Sacramento, San Joaquin, and Tulare basins. Note large groundwater depletion typical of the Tulare Basin.

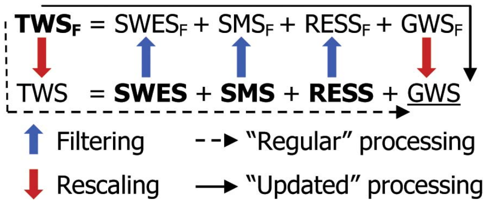

Figure 2. Synthesis of regular and updated methods for processing GRACE data to extract changes in GWS. Subscript F represents spatial filtering, applied equivalently to GRACE and water budget data (SWES, SMS, and RESS), i.e., truncation to degree 50 (GRGS) and degree 60 (CSR), removal of north-south stripes (for GRACE data only), and 300 km Gaussian filtering (CSR). Regular processing involves filtering GRACE data to estimate TWS, rescaling TWS using bias and leakage correction based on LSMs, and subtraction of changes in SWES, SMS, and RESS to calculate changes in GWS. Updated processing calculates changes in GWS from TWS using filtered models and data at GRACE resolution and rescaling GWS_F to GWS using bias correction, no leakage correction required. The updated approach also uses spatial variability of SWES, SMS, and RESS within the area of interest rather than mean values as in the regular approach. Bolded text refers to available data from GRACE or models.

as shown in Figure 2. This processing is described in detail in Auxiliary Material (section 1).[1]

[10] Changes in TWS are estimated from GRACE data by recombining spherical harmonics up to degree 50 (truncation to degree 50) for GRGS and to degree 60 for CSR. Further filtering was applied to CSR data to remove north-south stripes [*Swenson and Wahr*, 2006] and to reduce high frequency noise (300 km Gaussian smoother). No further filtering beyond truncation at degree 50 was applied to GRGS data because there are no north-south stripes and the regularization process used on GRGS precludes the need for additional filtering. In the following, filtering will refer to both truncation and filtering.

[11] Because filtering removes TWS signal at small spatial scales, in addition to high-frequency noise, the amplitude of the TWS signal has to be restored. Most studies calculate a rescaling or multiplicative factor to restore the signal amplitude by applying the same filtering as applied to GRACE data to a synthetic mass distribution and calculating the ratio between filtered and unfiltered data. Applying filtering to a synthetic mass distribution is sometimes referred to as "forward modeling" and generates a mass distribution similar to what GRACE sees. Ideally the synthetic mass distribution should match the actual mass distribution as closely as possible. For TWS, this mass distribution should include all components of the water budget. The synthetic mass distribution is generally derived from Global Land Data Assimilation System (GLDAS) land surface models (LSMs), such as CLM, MOSAIC, NOAH, and VIC. Output from the LSMs is generally used as a proxy for the true water mass distribution. The reliability of LSM outputs depends on the ability of the LSM to approximate the true water mass distribution in the system. LSMs are simplifications of the natural system with limited resolution and most simulate snow and soil moisture storage but generally do not include surface water or groundwater storage. Runoff is simulated but is not routed, and cold processes are not simulated accurately (especially glaciated areas). Water redistribution from groundwater to soils through irrigation is also not simulated in most LSMs. The signal restoration process uses spatial variability from LSMs, which may or may not be realistic and could lead to biased estimates in TWS [*Longuevergne et al.*, 2010]. Once the TWS signal is restored, the various water balance components, including SWES, RESS, and SMS basin averages, are then subtracted from TWS to calculate GWS as a residual (Figure 2). Therefore, this regular processing approach does not consider spatial variability of masses in a basin and uses a rescaling factor based on a priori LSM masses that ignore GWS.

2.3. Updated GRACE Processing

[12] GRACE processing was updated in this study to provide more reliable estimates of GWS changes with optimal use of available information. The new processing approach differs from the regular approach in calculating GWS from TWS using filtered data at GRACE resolution before any rescaling is applied (Figure 2). In this updated approach, GRACE data were recombined and filtered to provide filtered TWS, as previously described. The various water balance components (SWES, SMS, and RESS) were then filtered in the same way as GRACE data, i.e., projection of model grids on spherical harmonics, recombination to maximum degree 50 for comparison with GRGS data or degree 60 for comparison with CSR data and application of a 300 km Gaussian filter for comparison with CSR data. Gridded SWES and SMS data and point RESS data were used, allowing spatial variability in these different storage components to be incorporated in the processing, in contrast to the regular processing approach, which uses basin means. Restoring the amplitude of the filtered GWS signal only requires bias correction (simple rescaling) and no leakage correction (no external groundwater masses leaking into the area of interest) because GWS changes are assumed to be concentrated inside the aquifer; therefore, errors associated with leakage corrections should be minimized. Bias correction was done using a multiplicative factor that was calculated from the ratio of unfiltered to filtered GWS changes from output from the USGS Central Valley hydrologic model. This is important because GWS changes are highly variable spatially, i.e., $\sim$10 times greater in the Tulare Basin in the south than elsewhere in the Central Valley [*Faunt*, 2009]. This updated processing approach minimizes reliance on a priori information and allows GRACE to be used as independent observational data as much as possible. However, this updated approach requires knowledge of changes in SWES, SMS, and RESS inside and outside the basin and the quality of the GWS changes still depends on the quality of the models for these water balance components. Computation of GWS is independent of the TWS calculation at basin scale.

[13] Spatial distribution of water masses may differ among storage components and may have different signatures at GRACE resolution (i.e., filtered). For example,

[1]Auxiliary materials are available in the HTML. doi:10.1029/2011WR011312.

SMS is more or less distributed uniformly over the area of interest; however, SWE is concentrated in the mountains, generally at the edge of the basins, while GWS may be focused in on one part of the basin. The importance of considering spatial variability in mass variations within the different storage components on GRACE GWS changes is shown by comparing the different multiplicative factors for converting filtered storages to true storages calculated separately for each component of the water budget. The equivalent multiplicative factor to restore the GRACE signal for GRGS (CSR) varies by up to 15% depending on spatial variability in water mass distribution (2.69 for GRGS (4.94 for CSR)) multiplicative factor for SWES, i.e., unfiltered SWES divided by filtered SWES, 2.30 (4.29) for RESS, 2.58 (4.74) for SMS, and 2.37 (4.28) for GWS). The more concentrated the mass distribution, the lower the multiplicative factor. Therefore, use of a single multiplicative factor applied to TWS in the regular processing approach ignores spatial variability in water storage in each of the components and increases propagation of uncertainties in GRACE GWS estimates.

2.4. Water Storage Components and Uncertainties

[14] The following describes each of the water storage components and estimation of uncertainties. Changes in TWS over the Central Valley river basins were estimated from CSR and GRGS data, as described previously and also in more detail in Auxiliary Material (section 1). TWS was not used directly to calculate GWS but was only estimated to evaluate temporal variability in TWS in the system. Uncertainties in TWS changes were estimated from GRACE measurement uncertainties derived from residuals over the Pacific Ocean at the same latitude as the Sacramento and San Joaquin River basins [*Chen et al.*, 2009] with a magnitude of 18 mm for GRGS and 22 mm for CSR. While GRACE is corrected from Glacial Isostatic Adjustment (GIA) using the ICE5G PGR model from *Paulson et al.* [2007], impacts of GIA in the Central Valley are minimal.

[15] Uncertainties in GWS were estimated from propagating errors in SWE, RESS, and SMS from LSMs into GWS changes, resulting in 10 days (for GRGS) and monthly (for CSR) errors in GWS with a magnitude of 55 mm for GRGS and 67 mm for CSR. As the rescaling or multiplicative factor has a direct impact on the amplitude of GWS changes, we also computed an error estimate on the bias correction for GWS. Sources of uncertainty in the multiplicative factor are twofold: (1) numerical calculation in the integration process, estimated to be $\leq$1% when integrating on a 0.25 degree grid [*Longuevergne et al.*, 2010], and (2) uncertainty in mass distribution within the area of interest. For the latter uncertainty, the multiplicative factor was calculated with different realistic mass distributions: USGS Central Valley hydrologic model, considering simulated mass depletion in the different subbasins during the previous droughts and well analysis (see later), considering spatial variability in water level variations, variability in specific yield, or multiplication of both. Variability among computed multiplicative factors is $\sim$6%.

[16] Water storage changes from snow cover were based on snow data assimilation system (SNODAS). Because SNODAS assimilates ground-based snow water equivalent (SWE) estimates in California [*Barret*, 2003], it is considered the most reliable model for this study. As SNODAS output is only available after October 2003, the time series was supplemented with SWE output from the National Land Data Assimilation System (NLDAS) MOSAIC LSM, rescaled with SNODAS data. The scaling factor was calculated by comparing standard deviations from SNODAS and NLDAS MOSAIC SWE for overlapping times. Uncertainties in SWES were estimated from variability between SNODAS and scaled NLDAS MOSAIC model. Calculated monthly uncertainties in SWES are 28 mm based on differences between the models; however, calculated uncertainties do not include potential model bias.

[17] Variations in surface water reservoir storage were estimated from changes in water storage in the 26 largest reservoirs in the Sacramento–San Joaquin basins (California Department of Water Resources (see http://cdec.water.ca.gov/)) (Auxiliary Material, section 2, Table S1). Because information on uncertainties in reservoir storage volumes is not available (only uncertainties in water level changes of $\sim$3 mm from California Department of Water Resources), a conservative estimate of 10% reservoir volume error was assumed. To estimate changes in soil moisture storage, output from GLDAS LSMs (MOSAIC and VIC at 1° resolution and NOAH at 0.25° resolution) and NLDAS (MOSAIC at 0.125° resolution) were averaged. Uncertainties in SMS were estimated from variability among the LSMs ($\sim$ 3 mm yr^{-1}). *Kato et al.* [2007] showed that the variability among GLDAS models is greater than variability among forcing datasets and that the root-mean-square (RMS) error of SMS from the LSMs can be used as a conservative estimate of SMS uncertainty.

[18] Trends in each of the water budget components were calculated to estimate storage depletion in response to the drought. Various temporal filters were applied to assess their impact on calculated water storage changes. Some suggest that the raw data should be used to estimate trends; however, most studies apply a temporal filter to remove seasonal fluctuations and high-frequency noise to estimate long-term trends. One filtering approach was to remove seasonal components of the data series using a six-term harmonic series (sine and cosine periodic waves with annual, semiannual, and 3 month periods). A centered 12 month moving average was also applied. A fourth-order Butterworth low-pass filter was finally tested. Trends in water storage changes and associated standard errors were estimated using weighted linear least squares regression, considering the inverse of squared errors in the weighting process.

2.5. Groundwater Level Data

[19] Groundwater data were obtained from the California Department of Water Resources (see www.water.ca.gov/waterdatalibrary) to estimate GWS changes for comparison with GRACE-based estimates (Figure 1). The Central Valley includes a shallow unconfined aquifer and deeper confined aquifers [*Faunt*, 2009]. The unconfined aquifer provides water through drainable porosity related to water table decline times aquifer storage coefficient, termed specific yield. In contrast, the confined aquifer provides water through compressibility of water and the skeletal matrix and the aquifer storage coefficients are orders of magnitude less than those in the unconfined aquifer. In this analysis we focused on water storage changes in the unconfined

aquifer because they are generally greater than those in the confined aquifer and many wells penetrate both aquifers, increasing hydraulic connectivity between the unconfined and confined systems [*Faunt*, 2009]. Changes in GWS were computed from water-level time series from wells using the Karhunen-Loève transform which extracts the temporal signal in the regional groundwater behavior from a set of well observations with local representativity [*Longuevergne et al.*, 2007]. Other terms used to describe KLT analysis in different fields include singular value decomposition (SVD) and empirical orthogonal functions (EOFs). Linear interpolation was used to recompute seasonal variations because KLT requires monitoring data for the same dates. The first three eigenvectors, which account for ~80% of the total variance, were considered. Kriging was used for analysis of spatial variability in water level data.

[20] To evaluate results of the KLT well analysis, we compared GWS changes from well data with storage changes estimated from a groundwater model of the Central Valley that simulated flow from 1962 through 2003 [*Faunt*, 2009]. While this comparison is not a true test of the KLT well analysis approach because the water level data were used in the groundwater model calibration, the Central Valley hydrologic model provides a much more comprehensive description of the groundwater system and this comparison provides a check on the well analysis technique. While data from 2256 wells are available, this analysis requires temporally continuous data; therefore, only 670 wells were used from 1982 through 2010. Selected wells are generally sampled twice a year, during high and low water times, allowing general reconstruction of seasonal variations. Mean groundwater level changes over the aquifer were then computed using kriging and GWS changes were derived considering distributed specific yield data from *Faunt* [2009]. A 10% uncertainty in specific yield data was also included because there are no published estimates on uncertainties in specific yield. Relative errors from the two sources of uncertainties were added up (10% specific yield, 2% kriging).

3. Results and Discussion

[21] Changes in precipitation are one of the primary drivers of water storage variations. Precipitation anomalies from 2002 through 2010 ranged from −11 to −69 mm during 2002 through 2004 but were high (surplus) during 2005 (227 mm) and 2006 (110 mm) (Figure 3). Negative precipitation anomalies (deficit) were recorded during the drought with the lowest values in 2007 (−259 mm) with lesser deficits in 2008 (−155 mm) and 2009 (−81 mm). The drought ended in 2010 with a positive precipitation anomaly of 290 mm.

[22] Monthly TWS changes from GRGS and CSR TWS are highly correlated ($r^2 = 0.93$) and amplitude ratios are close to one, even after removal of seasonal variations (Figure 3). Moreover, the difference between CSR and GRGS TWS time series (~26 mm) is slightly larger than, but very similar to, estimated monthly RMS errors (18 mm for GRGS and 22 mm for CSR). Similarity in TWS changes from GRGS and CSR increases confidence in GRACE output from different processing centers. TWS changes are highest in spring (February/March) and lowest in fall (September/October) with amplitudes ranging from 15 to 30 km^3 at different times. TWS changes were relatively uniform during 2002 through 2004 and increased by ~15 km^3 (April 2004 through March 2006, GRGS and CSR) in response to increased precipitation. Depletion in TWS during the drought was greatest during the beginning of the drought, when precipitation was lowest in 2007 (−259 mm). The drought has been documented to persist during water years 2007 through 2009 (i.e., October 2006 through September 2009) [*Jones*, 2010]. The maximum depletion in

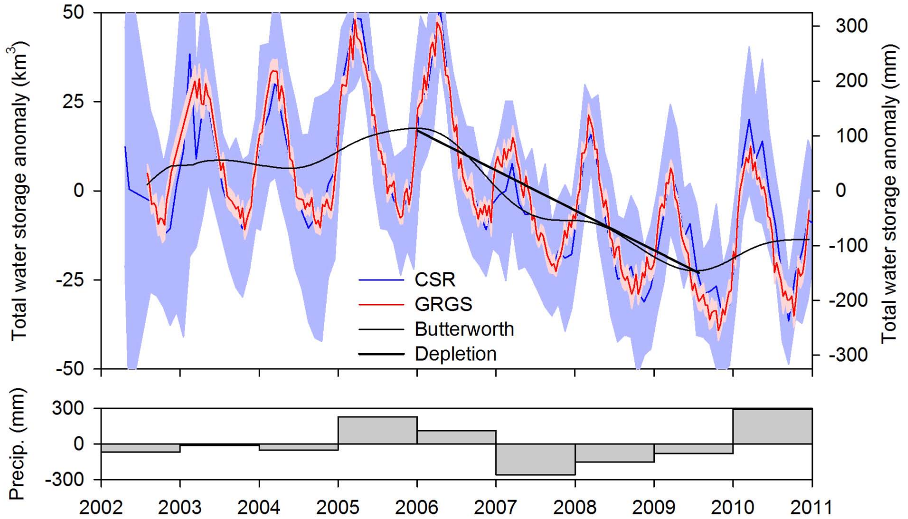

Figure 3. Total water storage (TWS) change anomaly (in km^3 and mm of water) from CSR monthly data and GRGS 10 day data for the Sacramento and San Joaquin River basins. Shaded areas represent monthly errors. Estimation of TWS is described in Auxiliary Material (section 1). A Butterworth filter was applied to the GRGS data to remove the seasonal signal and high-frequency noise. The depletion trend during the drought is shown (40.8 km^3 from January 2006 through July 2009). The precipitation anomaly is based on gridded data from PRISM [*Daly et al.*, 2010].

TWS occurred from January 2006 through July 2009 and ranged from 39.0 ± 2.5 km^3 (CSR) to 40.8 ± 0.9 km^3 (GRGS) based on a Butterworth filter to remove seasonal signals and high-frequency noise. Different filters were evaluated; however, errors in the Butterworth filter were among the lowest (Auxiliary Material, section 3, Figure S1).

[23] The largest reductions in snow water equivalent and soil moisture storage occurred during the winter of 2006–2007 because this was the driest period of the drought (Figure 4). The snowpack reservoir decreased markedly during the winter of 2006–2007 but increased after that resulting in essentially zero overall change in storage during the drought. Surface water reservoir storage from the 26 largest reservoirs decreased by 7.3 ± 0.6 km^3 from October 2006 through September 2009. The largest reductions in simulated SMS from the various LSMs also occurred during the first year of the drought with recovery after that time. Simulated changes in SMS may not be highly reliable because the LSMs do not simulate redistribution of water from the aquifer to the soil zone from irrigation.

3.1. GRACE Estimates of GWS Changes and Comparison With Groundwater Level Data

[24] While the GWS change signal varies around that of TWS (standard deviation TWS [CSR and GRGS] 20 km^3; GWS CSR 21 km^3; GWS GRGS 13 km^3), uncertainties in GWS changes are about a factor of three higher than those in TWS (RMS errors: CSR: GWS 10.2 km^3; TWS 3.3 km^3; GRGS GWS 8.4 km^3; TWS 2.8 km^3). The following discussion focuses on GWS changes from GRGS data because they are less noisy than those from CSR data (Figure 5; Auxiliary Material, section 4, Figure S3). The temporally filtered GWS data show that GWS increased slightly from April 2004 through March 2006 (2.7 ± 0.5 km^3) when precipitation was high. However, GWS decreased sharply during the drought by 31.0 ± 3.0 km^3 from October 2006 through March 2010 (Table 1). Use of raw data resulted in depletion of only 5.1 km^3, showing the importance of temporally filtering the data to remove seasonal signals and high-frequency noise. The Butterworth and centered 12 month moving average filters provided similar results, whereas the seasonal sine/cosine function did not smooth the data and resulted in the largest errors (±5 km^3) (Auxiliary Material, section 3, Figure S2). Mean GWS depletions from this study are 16% (27.7 ± 5.2 km^3 CSR) and 44% (34.4 ± 3.2 km^3 GRGS) higher than that based on analysis by *Famiglietti et al.* [2011] for CSR (23.9 ± 5.8 km^3) for the same time period (April 2006 through March 2010). Therefore GWS depletions during the drought in this study are within the error bars for CSR data and slightly higher for GRGS data relative to the estimate from *Famiglietti et al.* [2011].

[25] Although there is a seasonal component to the GRACE based GWS changes (~30 mm) for GRGS, ~47 mm for CSR, which is below the 10 day to monthly error estimate (GRGS 55 mm; CSR 67 mm), it is not considered reliable because it is the residual of seasonal fluctuations in other water balance components, including SWES, RESS, and SMS, and reflects uncertainties in seasonal storage changes in these components with associated phase lags that can result in large differences after subtraction.

[26] GWS changes were also calculated from well data by converting water level changes to water volumes using spatially distributed specific yield (Figure 6). Typical well hydrographs for the different basins indicate minimal water level declines in the north and all declines focused in the Tulare Basin in the south (Figure 1). GWS changes using KLT for time series analysis and kriging for spatial variability in this study compared favorably with simulated GWS changes from the Central Valley hydrologic model for the overlap period of the groundwater model (r^2 = 0.98; Figure 7). Well analysis for the 1987–1992 drought yielded a GWS decline of 8.2 km^3 yr^{-1}, similar to the simulated GWS decline from the model of 8.2 km^3 yr^{-1}. This comparison gives confidence in the KLT/kriging approach used to analyze the well data. Although the Central Valley model also used the well data for calibration, the model represents a much more comprehensive evaluation of the groundwater system.

[27] To compare GWS changes from the well data with those from the GRACE data, groundwater depletion from the well data was forward modeled to determine what GRACE can see (Auxiliary Material, section 5, Figure S4). The same spatial filtering was applied to the well data as is applied to GRACE products (Figure 2). Although there is 10 times more depletion in the Tulare Basin in the southern part of the Central Valley, it is not possible to determine this at GRACE resolution (Figures S4a and S4b). The GWS anomaly is spread above the Central Valley aquifer, shifted toward the south. Spatial trends in GWS depletion from CSR and GRGS data (Figures S4c and S4d) generally correspond to the modeled impact of depletion on groundwater (Figures S4a and S4b), with equivalent amplitude and position. In addition to using standard errors in trend estimates of GWS from GRACE and well data, we also

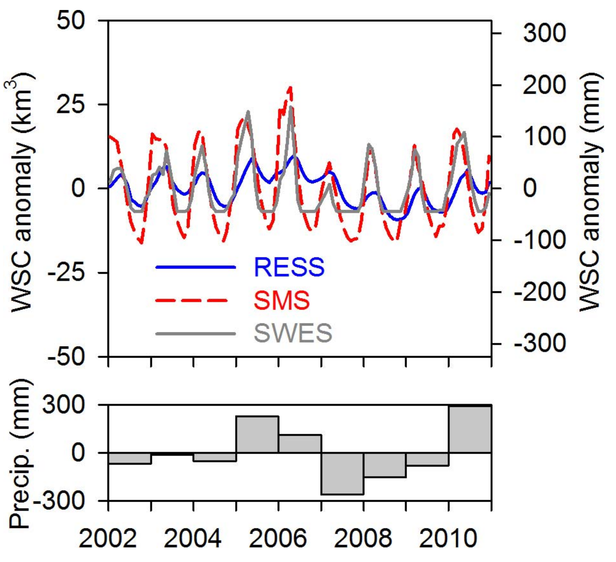

Figure 4. Surface water reservoir storage (RESS), snow water equivalent storage (SWES), and soil moisture storage (SMS) change anomalies for the Sacramento and San Joaquin River basins. Note large reduction in water storages in response to the 2006 through 2009 drought, particularly in the first year of the drought. The precipitation anomaly is based on gridded data from PRISM [*Daly et al.*, 2010].

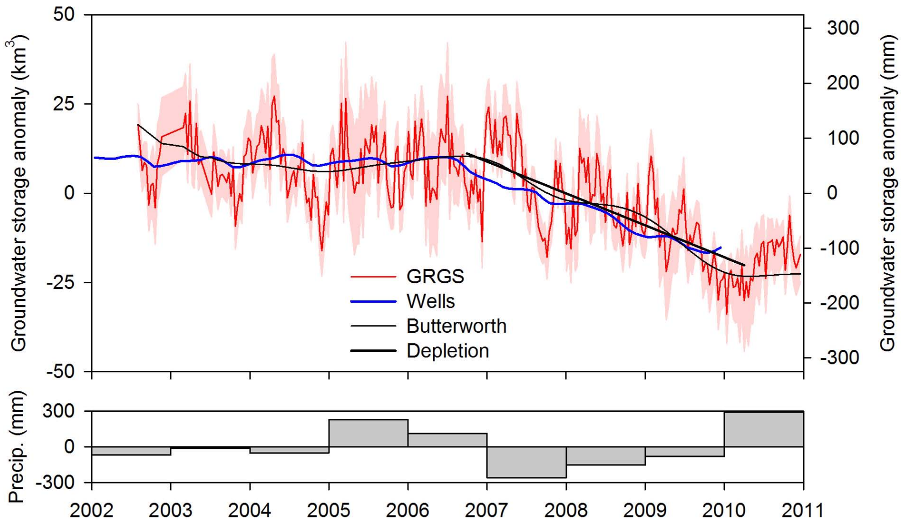

Figure 5. GWS change anomaly from GRGS data and monthly changes in GWS from well data from the upper unconfined aquifer. GWS change anomalies for CSR and GRGS data are shown in Auxiliary Material, section 4, Figure S3. A Butterworth filter for removal of seasonal trends and high-frequency noise is shown. Application of other filters is shown in Auxiliary Material, section 3, Figure S2. Depletion during the drought (31.0 ± 3.0 km^3) is shown from October 2006 through March 2010. The precipitation anomaly is based on gridded data from PRISM [*Daly et al.*, 2010].

estimated the GWS signal in the oceans for the same area as the Central Valley. The signal in the ocean should be zero if all background models for mass disaggregation were perfect (oceanic and atmospheric model in GRACE processing, SWES, SMS, and RESS for GWS extraction); therefore, nonzero values suggest errors in GWS of $\sim$30% of groundwater depletion after integration over an area as large as the Central Valley river basins. These error estimates may be more reliable than the standard errors in trends and in multiplicative factors, which probably underestimate total error. While the main negative GWS anomaly is located above the Central Valley aquifer, it is shifted toward the mountains for both GRGS and CSR solutions. The north-south trending anomaly along the mountain range suggests that snow water equivalent was not properly corrected for when the GWS contribution was extracted.

[28] Because the well data only extend to December 2009, GWS changes from the well data were compared with GRACE-based estimates for the period April 2006 through September 2009 to avoid problems with filtering toward the end of the data record (Table 1). Groundwater depletion from the well data is the same as that from GRACE GRGS data (both $\sim$27 km^3) for the 3.5 year period (Table 1). These comparisons indicate that the GRACE based estimates of GWS changes are generally consistent with those from well data.

[29] Reduction in GWS from GRACE during the recent drought (8.9 km^3 yr^{-1}) is similar to GWS reductions from

Table 1. Trends in Groundwater Storage Changes During the Drought in mm yr^{-1}, km^3 yr^{-1}, and in Total km^3 for the Different Time Periods Shown Based on GRGS and CSR GRACE Data and Well Data[a]

Model	Filter	Trend (mm/a)	Error (mm/a)	Trend (km^3/a)	Error (km^3/a)	Volume (km^3)	Error (km^3)
				1 Oct 2006 through 31 Mar 2010			
GRGS	Butterworth	57.6	5.5	8.9	0.8	31.0	3.0
GRGS	Moving average	58.1	5.6	8.9	0.9	31.3	3.0
GRGS	Seasonal	57.8	9.2	8.9	1.4	31.2	5.0
GRGS	None	9.4	–	1.4	–	5.1	–
				1 Apr 2006 through 31 Mar 2010			
GRGS	Butterworth	55.9	5.3	8.6	0.8	34.4	3.3
CSR	Butterworth	44.9	8.5	6.9	1.3	27.7	5.2
				1 Apr 2006 through 30 Sep 2009			
GRGS	Butterworth	49.9	4.8	7.7	0.7	26.9	2.6
Wells	Butterworth	49.7	0.5	7.7	0.1	26.8	0.3

[a]Well data are from 920 wells from the monitoring network. Depletion trends for different time periods and associated standard errors were estimated using weighted linear least squares regression, considering the inverse of squared errors (monthly for CSR and 10-day intervals for GRGS) in the weighting process. From 1 October 2006 through 31 March 2010 represents the maximum depletion of GWS during the drought (Figure 5). Trends from 1 April 2006 through 31 March 2010 were calculated for comparison with depletion estimates from *Famiglietti et al.* [2011]. Trends from 1 April 2006 through 30 September 2009 were calculated to compare depletion estimates from GRACE with those from analysis of 920 wells (Figure 5). Results from application of different filters to remove seasonal fluctuations and high-frequency noise are provided, including Butterworth, centered 12 month moving average, a six-term harmonic series (sine and cosine periodic waves with annual, semiannual, and 3-month periods; Seasonal), and no temporal filter (trend from raw data).

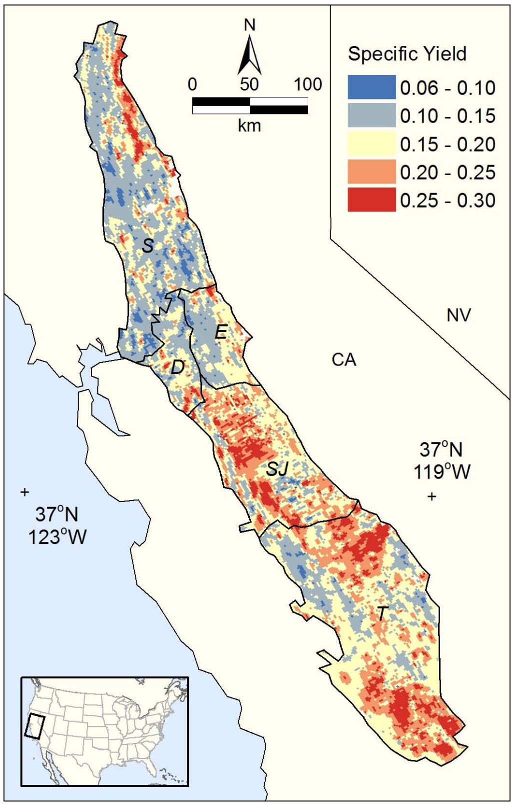

Figure 6. Variations in specific yield from *Faunt* [2009].

previous droughts from the Central Valley hydrologic model (1976–1977, 12.3 km^3 yr^{-1}; 1987–1992, 8.2 km^3 yr^{-1}). Although precipitation during the recent drought was not as low as the 1976–1977 drought and the length of the recent drought was much shorter than the 6 year drought from 1987 through 1992, the impact of the recent drought on GWS was as large as or larger than that of previous droughts because surface water diversions from north to south were reduced to 10% by the third year of the drought to protect the endangered delta smelt species in response to the Central Valley

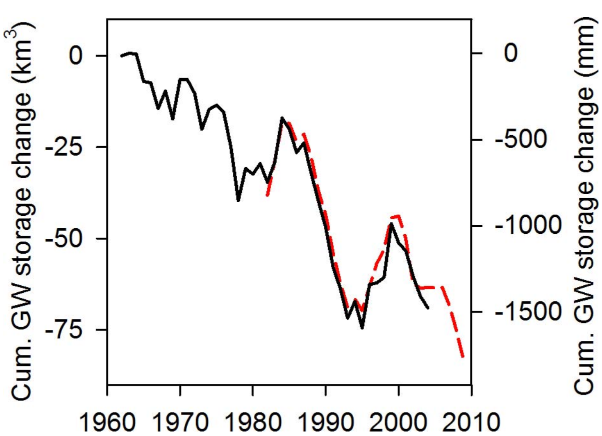

Figure 7. Comparison of GWS changes from well analysis relative to simulated GWS changes from the Central Valley hydrologic model (CVHM) [*Faunt*, 2009]. Drought periods are shaded (1976–1977, 1987–1992, and 2006–2009).

Improvement Act of 1992 [*California Department of Water Resources*, 2010]. Reductions in surface water diversions resulted in large increases in groundwater pumpage and amplified the impact of the drought on GWS changes.

3.2. Future Work

[30] There are many areas of potential future work that would improve application of GRACE data for monitoring water storage changes in the Central Valley region. Updating the Central Valley hydrologic model to include the time period evaluated by GRACE would provide another estimate of GWS changes for comparison with GRACE-based estimates. This work is currently being conducted by the U.S. Geological Survey (C. Faunt, personal communication, 2011). Improving the ground-based well monitoring network would greatly enhance estimates of GWS changes from this data set. Basic information on wells, such as length and depth of screened intervals and whether wells penetrate only unconfined aquifers or unconfined/confined aquifers would be very helpful. Additional information on storage coefficients for converting water level data to water volumes is extremely important in this type of analysis. Expanding the well network, particularly in the Tulare Basin in the south, where most of the depletion has occurred, and including more continuous monitoring of water levels would provide improved information for estimating GWS changes. Information on soil moisture currently relies on output from LSMs; however, these models do not simulate irrigation. Developing a ground-based network of soil moisture sensors would be very beneficial for application to GRACE studies and would also provide a comparison of output from LSMs. Because LSMs play an integral role in GRACE processing, reliable water storage change estimates from GRACE depend on accurate LSMs. Improving LSMs to simulate soil moisture, groundwater, and irrigation is very important for applications of GRACE to groundwater depletion studies related to irrigated agriculture. The study of *Famiglietti et al.* [2011] used unconstrained CSR GRACE data whereas this study also used constrained or regularized GRGS GRACE data. The next GRACE CSR release will include some type of regularization or constraint [*Save et al.*, 2010]; therefore, filtering beyond truncation may no longer be required and spatial resolution may be improved.

4. Conclusions

[31] While the area of the Central Valley aquifer is less than the GRACE footprint (~200,000 km^2), extensive groundwater depletion caused by irrigation results in a large signal that can be detected by GRACE. A new processing approach was applied to GRACE data that calculates changes in GWS from TWS by subtracting SWES, RESS, and SMS using filtered data at GRACE spatial resolution minimizing uncertainties associated with LSMs for bias and leakage corrections. Moreover, this method takes into account the specific spatial distribution of each water storage component (including SWES, SMS, and RESS) resulting in different signatures on GRACE. In the case of the Central Valley, availability of high-resolution validated models (SNODAS, NLDAS) and accurate ground measurements for surface water storage reservoirs greatly improved the ability to resolve GWS changes for this relatively small basin.

[32] TWS changes from GRGS and CSR processing centers were similar ($r^2 = 0.93$). Reductions in TWS during the drought ranged from 39.0 ± 2.5 km^3 (CSR) to 40.8 ± 0.9 km^3 (GRGS) (Butterworth filter) (January 2006 through July 2009). SWES and SMS decreased markedly in the early phase of the drought (2006–2007) but partially recovered after that, resulting in overall negligible to low water storage changes. Reservoir storage decreased continuously during the drought by 7.3 ± 0.6 km^3 (October 2006 through September 2009).

[33] Analysis of GWS changes focused on GRGS data because CSR data are noisier. GWS declined by 31.0 ± 3.0 km^3 based on maximum depletion from October 2006 through March 2010. Annual decline rates (8.9 $km^3\ yr^{-1}$) are consistent with typical decline rates from previous droughts (1976–1977, 12.3 $km^3\ yr^{-1}$; 1987–1992, 8.2 $km^3\ yr^{-1}$). GRACE based estimates of groundwater depletion during the drought are similar to those from well data based on the uppermost unconfined aquifer for the overlap period (6 April through 9 July; both 27 km^3). The general consistency of GWS changes from GRACE and ground-based estimates increases confidence in application of GRACE for monitoring groundwater depletion.

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